Journal of Fuzzy Extension and Applications

www.journal-fea.com

J. Fuzzy. Ext. Appl. Vol. 6, No. 3 (2025) 484–505.

Paper Type: Research Paper

Integrating Hesitant Fuzzy Sets with Machine Learning for Enhanced Healthcare Predictive Analytics

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Citation:

Received: 26 November 2024 *Revised: 28 February 2025* *Accepted: 29 April 2025*	Rajagopal, M., Mandala, G., Ranganathan, N., Varthan Velumani, M., Patro, P., & Arumugam, Sh. (2025). Integrating hesitant fuzzy sets with machine learning for enhanced healthcare predictive analytics. *Journal of fuzzy extension and applications, 6*(3), 484-505.

Abstract

This study examines how Hesitant Fuzzy Sets (HFS) and Machine Learning (ML) might improve healthcare predictive analytics. HFS, which accommodates uncertainty and hesitation in decision-making, is used to improve healthcare projections. Predictive analytics methods struggle with data ambiguity and imprecision, resulting in poor decision-making. Traditional ML algorithms may not be able to collect hesitant information, resulting in less accurate patient outcomes and treatment recommendations. The Integrating Hesitant Fuzzy Sets with ML (IHFS-ML) framework overcomes these issues by integrating HFS flexibility with advanced ML approaches. This connection allows the representation of ambiguous patient data for better healthcare analytics. Data pre-processing in the IHFS-ML framework improves healthcare analytics prediction. These methods transform uncertain fuzzy data into an ML-friendly format. Disease prediction, patient risk assessment, and therapeutic effectiveness analysis are recommended. The approach aims to improve healthcare decision-making and deliver new insights by merging hesitant and ambiguous information. IHFS-ML uses HFS to characterize imprecise and confusing patient data. These HFS are combined with powerful ML classifiers like Random Forest (RF) and Logistic Regression. The IHFS-ML system outperforms current prediction accuracy and reliability methods, suggesting it might transform healthcare analytics. HFS improves ML model interpretability, improving patient outcomes and healthcare decisions. Compared to other methods, the IHFS-ML model improves prediction analysis reliability by 99.7%, scalability by 97.6%, data pre-processing efficiency by 97.1%, interpretability by 98.9%, and accuracy by 97.8%.

Keywords: Hesitant fuzzy sets, Machine learning, Healthcare, Patient data, Clinical decision-making.

1 | Introduction

Compared to these, traditional methods have various challenges in combining Hesitant Fuzzy Sets (HFS) with Machine Learning (ML) to improve predictive analytics in health domains [1]. Generally, healthcare data

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https://doi.org/10.22105/jfea.2025.490702.1715

is complex, involving overlapping and confusion with missing values; hence, fuzzy techniques face problems. Fuzzy logic models are not expert-dependent and require an accurate membership function identifying characteristics with this property [2]. It becomes difficult to set membership functions manually, and biases may restrict access to large, dynamic datasets like healthcare [3]. Traditional methods like type-1 fuzzy sets cannot identify human judgment uncertainty. These methods barely represent the uncertainty of clinical decision-making [4]. Thus, one might hazard an educated guess that expert and database opinions and assessments could be underrepresented. Another challenge or difficulty involves combining classical fuzzy models with ML. Fuzzy-based reasoning may fail for ML models such as decision trees, neural networks, and support vector machines due to their requirement for clean input data [5]. Fuzzy data in machine-learning formats can result in the loss of information and may lower the accuracy of predictions. Traditional fuzzy logic models cannot scale for huge datasets in real-time healthcare analytics [6]. These disadvantages necessitate sophisticated integration techniques, like HFS, to build more predictable ML and develop better approaches for dealing with uncertainty and unpredictability in healthcare [7]. As healthcare data grows in volume and complexity, these limits highlight the need for more advanced integration methods.

Healthcare data ambiguity and imprecision make managing one of the primary challenges more difficult [8]. Different levels of clinical judgment and diagnosis doubt are common. HFS can describe this reluctance with different membership values; however, ML models struggle to absorb this data [9]. Since ML systems are meant to handle crisp or probabilistic data, it isn't easy to directly incorporate HFS's sensitive and fuzzy nature. As new or modified algorithms are created, algorithmic complexity increases. Interpreting HFS-based models is another machine-learning difficulty [10]. This is especially troublesome in healthcare, where judgments must be transparent. HFS-based real-time data processing models are challenging to scale. Since healthcare data is large and constantly generated, models that evaluate data rapidly and accurately are essential [11]. A fundamental difficulty for HFS-based models is handling huge datasets efficiently and with minimum computational overhead. We need more accurate, easy-to-understand hybrid modeling methodologies and more efficient healthcare application frameworks that consume less processing resources to handle these difficulties [12].

HFS integrated with ML improves healthcare predictive analytics. A hybrid model combines HFS's uncertainty management strengths with current ML [13]. These models use HFS's ability to describe several degrees of membership to effectively depict healthcare data's subtle uncertainty. When combined with HFS, neural networks, or decision trees, models can accommodate clinical data ambiguity and varied perspectives [14]. Forecasts are more accurate and forceful. Introducing hesitant fuzzy data straight into ML algorithms is another option. Feature extraction strategies that convert HFS into machine-readable input may be unique. This strategy integrates with existing ML methods without costly data translation while keeping fuzzy information. To simplify data, fuzzy rule-based systems and ML operate together. Doctors can grasp the models' projections, making them more trustworthy. Cloud computing and parallel processing can reduce HFS-integrated model computational problems and improve scalability. The healthcare business can manage huge databases and real-time analytics for early diagnosis and therapy monitoring. HFS-specific software tools and libraries could simplify its use for researchers and practitioners. Overall, these solutions bridge HFS theory and healthcare applications.

The present research examines healthcare data and predictive analytics ambiguity and resistance. Traditional machine-learning approaches struggle to organize this data. Patient data ambiguity, imprecision, and resistance complicate the clinical decision-making process. Existing predictive models struggle to include uncertainty, making patient outcomes, risk assessments, and treatment planning forecasts inaccurate. Due to this limitation, both decisions and outcomes in healthcare are influenced. Here, HFS and ML are required to handle the complexities of healthcare analytics.

Patient records, diagnostic criteria, and symptom evaluations often include ambiguous, incomplete, or otherwise difficult-to-handle data, which traditional healthcare predictive analytics algorithms have difficulty dealing with. For example, standard crisp logic-based models are not very good at handling symptoms like

"occasional chest pain" or "moderate fatigue" because of the language ambiguity they include. To overcome these shortcomings, HFS represents several membership degrees for a single element, accurately representing clinical data's subjective and hesitant nature. In contrast to Intuitionistic Fuzzy Sets (IFS) and regular fuzzy sets, HFS allows for the simultaneous examination of all possible membership values without aggregating them into a single score, thereby maintaining important uncertainty information. HFS is suitable for healthcare environments with overlapping symptoms and conflicting expert diagnoses.HFS may capture hesitancy in expert evaluations and patient-reported data better than other fuzzy techniques, resulting in more accurate and context-aware predictive modeling, which technically enables its use.

The Integrating Hesitant Fuzzy Sets with ML (IHFS-ML) framework's main innovation is its integration approach. Instead of addressing ML and fuzzy modeling separately, it methodically integrates HFS-based reasoning into the pipeline. This approach directly trains models using HFS-based representations. This contrasts with traditional methods that employ fuzzy pre-processing before feeding information into ML algorithms. HFS-based representations and varying degrees of membership exist in these feature vectors. Logistic Regression and Random Forest (RF) learning methods can adapt to feature distributions while considering uncertainty. This improves classification robustness in complex clinical settings. Data preparation uses reluctant fuzzy transformation as an extra layer. To transfer unlabeled language variables into structured HFS-based features, this layer uses hesitant fuzzy transformation instead of crisp discretization. Conventional approaches ignore this tiny resistance while producing features, resulting in data loss. IHFS-ML's innovative method outperforms standard ML and fuzzy-integrated baseline models in prediction tasks while retaining uncertainty propagation throughout the learning process.

The main contribution of the paper is:

I. Designing the HFS and ML to improve the forecasts of healthcare predictive analytics. This would have addressed the arena's ambiguity and hesitation.

II. Data preparation improves the predictive performance of health analytics and sorts ambiguous patient data. Both strategies make recalcitrant fuzzy data ML-friendly.

III. To determine how effectively the proposed IHFS-ML framework operates in various healthcare contexts, such as disease prediction, patient risk analysis, and evaluation of therapy efficacy, while comparing it with other traditional predictive techniques.

Complicated decision-making processes are now integrated into solving complex challenges in numerous fields. This is self-evident in most contexts, where uncertainty and ambiguity prevail. Mardani et al. [15] proposed a method to assess issues involved in DTs across the COVID-19 pandemic using a combination of the HFS approach with SWARA and WASPAS approaches. Analysis has shown that HIS is the most critical component. Mishra et al. [16] proposed a new Additive Ratio Assessment (ARAS) approach to be applied in the proposed methodology along with a divergence measure for HFS. Remdesivir emerges as the prime treatment for mild COVID-19 symptoms in this methodology. Alfakeeh et al. [17] introduced improving the security-durability of healthcare online applications incorporating self-reliant security features as the proposed method's objective using a hesitant fuzzy-based AHP-TOPSIS algorithm to analyze the security risks. Sahu et al. [18] proposed for ranking renewed energy sources, the proposed method utilizes a Hesitant Fuzzy Analytical Hierarchy Process (HFAHP). This procedure identifies landfill gas and biogas as the best alternatives on which decisions can be based for investments in sustainable energy.

Büyüközkan et al. [19] showed that the presented strategy is efficient in handling uncertainty and even surpasses HFL COPRAS and HFL TOPSIS in case of decision-making. The proposed methodology integrates hesitant fuzzy linguistic AHP and CODAS to analyze smart health solutions. Alattas and Wu [20] developed an extended hesitant fuzzy generalized TODIM methodology used in the proposed method to evaluate the challenges against the IoMT adoption. These are key challenges like regulatory affairs and vendor lock-in, which are pinpointed by this methodology, enhancing critical healthcare decision-making. Büyüközkan and Güler [21] have devised ranking SCA tools for which the introduced approach combines

HFLTS, HFL AHP, and HFL MULTIMOORA. Based on the results of the ranking job, PeopleSoft is announced as the best option, and the critical points of this solution have been mentioned in terms of the change in the statistical power and product quality improvement.

Iqbal et al. [22] suggested the Fermatean Probabilistic HFS (FePHFSs) for optimizing earthquake response. The creation of new Aggregation Operators (AOs) for Probabilistic HFS (PHFSs) by meticulous synthesis of algebraic operations using the Combined Compromise Solution (CoCoSo) technique is a significant step forward in the area of Multi-Attribute Decision-Making (MADM). The CoCoSo technique, noted for its resilience in optimum goal selection, is essential to this strategy for navigating difficult multi-criteria decision-making. This approach uses many aggregating methods. A comprehensive numerical case study shows how effective and adaptable this method is to real-world circumstances. PHFS and CoCoSo provide decision-makers with a new tool. This tool helps decision-makers make reliable, educated choices even in uncertain situations.

Habib Zare Ahmadabadi et al. [23] proposed the novelty of Hesitant Fuzzy TOPSIS and meta-synthesis for supply chain resilience. Management included production and distribution, communication and participatory management, financial and information resources, human resources, and risk and crisis. A total of 33 variables made up the model.

Ahmed et al. [24] recommended the intuitionistic hesitant fuzzy aggregation information and its application in decision-making problems. The first step is to suggest a potential degree measure that can be used to rank numerical values in the CIHFS setting. The next step is to create new AOs and operating rules. These AOs make many choices in a CIHFS framework possible. Not only that, but the research delves into MCDM as well, suggesting an approach that uses complex, intuitive, and fuzzy data.

Choudhary et al. [25] discussed the spherical hesitant fuzzy soft yager aggregation information for improved industrial control systems of decision-making. To examine these collections, the study expands upon Yager's parametric families of t-norms and t-conorms. This method is crucial for fixing MADM issues regarding ICS security. To achieve this goal, four separate AOs are suggested: geo-weighted averaging aggregation, ordered weighted averaging aggregation, weighted fuzzy soft yager, and geo-ordered weighted geometric aggregation. These operators are designed to use Yager's parametric families in an operational sense, providing a solid foundation for handling decision-making issues in uncertainty. In addition, we provide an algorithm that incorporates these AOs, which was developed especially for MADM.

Iqba et al. [26] delibrated the Fermatean Probabilistic Hesitant Fuzzy Hybrid Aggregation Information (FePHHWA) for enhanced airport security screening. These protocols aim to streamline decision-making by offering a comprehensive approach to handling the complexities of security screening. The proposed method demonstrates the efficacy and adaptability of FePHFSs and lays the groundwork for fixing airport security screening problems using the newly created hybrid aggregation procedures.

Safa et al. [27] presented the prediction of mental health using social media. This study is organized in a way consistent with feature extraction, data collection, and forecast algorithms. In addition, the author looks at several recent studies that have investigated various aspects of candidate profiles and the methodologies used to analyze them. The author then examines current and future developments in experimental auto-detection frameworks for disease identification, debating several elements of their evolution. Supplementing screening processes, identifying at-risk individuals via large-scale social media monitoring, and ease of future disorder treatment may be achieved using the provided approaches.

Rouhani Poor et al. [28] introduced the hybrid MCDM based on DANP in a hesitant fuzzy approach for measuring product quality. Given its focus on practical applications and quantitative research methods, the current investigation fits well into applied studies. Academics and professionals from the university industry make up the study's population. After considering intentional and snowball sampling strategies, we arrived at a sample size of ten. The Analysis Network Process (ANP) was integrated with the DEMATEL technique, which was combined with hesitant fuzzy logic. Then, the experts' uncertainty in determining the mutual

impact of product quality factors was considered, and the final model, DEMATEL-based ANP (DANP), was extracted. The current research may be considered novel because of this method.

Wanke et al. [29] offered the performance assessment and lockdown decisions of the UK healthcare system in dealing with COVID-19 using MCDM. The first step is to use software like TOPSIS or Complex Proportional Assessment (COPRAS) to calculate partial distances or utility functions. Secondly, the Latent Vagueness and Randomness Components (LAVRA) approach removes uncertain components from unbiased performance ratings. Third, drivers of lockdowns are categorized using performance, fatalities, and areas employing a bootstrapped neural network regression. The availability of ventilated beds is a crucial motivator, but staff absenteeism from COVID-19 and a high admission rate of senior inpatients are less significant. According to the data, TOPSIS yields performance scores between 0.65 and 0.75; however, COPRAS analysis considerably lowers the ratings.

Edalatpanah [30] suggested that the HFS solves the problem of choosing a strategy in uncertain conditions. This study finds the optimum choice by applying the scoring function to the matrix components of the robustness analysis and transforming them into hesitant fuzzy elements. An improved solution employing hesitant fuzzy components was obtained by applying the suggested method to four issues that had previously encountered difficulty selecting the optimal choice. Solving the issue of selecting a strategy concerning equal stability of choices requires developing the matrix method for robustness analysis.

Mehrabi et al. [31] proposed the HFS for decision-making regarding granting facilities to Sepah Bank loan applicants. This study suggested a straightforward distance-based technique to deal with experts' intuitive and inaccurate assessments, which were deemed reluctant fuzzy data. A comprehensive rating of financial institution loan applicants results from the suggested algorithm. There has been no previous research to provide a prioritizing method in this domain, and the decision-making dilemma given in this study is obvious.

Salam et al. [32] recommended the convoluted neural network for upper limb gestures recognition model for hearing and speech impaired patients. Data produced from upper limb motions was processed, detected, and recognized via a series of steps in the model's construction. Ratios of Relative Standard Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) were among the measures used to assess performance. Among the metrics measured by the CNN model assessment are a loss function of 0.2913, an accuracy of 78.73%, a precision of 0.8409, a recall of 0.7396, RMSE of 0.1127, MSE of 0.0127, and MAE of 0.0245. According to the results, CNN may be used to construct a model for gesture recognition. In addition, suggestions for further study on sign language identification and motions are made, and reinforcement learning is suggested as a tool for creating an embedded automated system.

Manoharan and Edalatpanah [33] presented evolutionary bioinformatics with a veiled biological database for healthcare operations. Individual bits are framed for further bioinformatics data processing components in the suggested method, and the design issues are accomplished with suitable transmitting and receiving modules. A plan that keeps the processing of huge data error-free. Since all channels may be accessed according to the framed bits, this architecture minimizes the overall error in the enormous data processing stage. In addition, utility rates are increased by maintaining all channels conveying bioinformatics data at high-quality bits, maximizing service quality. The suggested architecture was tested in five different situations to see how well it worked. According to the results, the suggested method can process healthcare bioinformatics data in real time with a 95% service quality guarantee.

Alkhatib et al. [34] introduced the impact of patient engagement on healthcare. The author provides a thorough evaluation, analysis, and synthesis of research published in the last five years in this article, systematically investigating the current literature on identifying the results and advantages of patient involvement in healthcare. From 2018 to 2023, we combed through the authorized topics, research difficulties, paper scopes, methodology, and major conclusions of the relevant literature. The authors were able to gather data from 28 research. We provide a study typology that outlines the key results and advantages of patient participation in the healthcare process of significant contemporary research in this area based on the objective analysis of the selected studies.

Phuong-Binh [35] examined the CNN and LSTM models to predict PM2.5 concentration in Vietnam. This article comprehensively overviews AI-IoT systems to manage healthcare data in smart cities. Key components such as predictive health analytics, remote patient monitoring, and the interoperability of healthcare systems are explored. The impact of these technologies on managing chronic illnesses, telemedicine, and smart city infrastructure will be analyzed, considering important aspects related to privacy and ethical concerns. Our findings suggest that AI-IoT systems promise to improve real-time patient monitoring and AI-driven diagnostic capabilities, thereby significantly transforming the healthcare landscape.

Chanda [36] analyzed the AI-driven IoT solutions for managing healthcare data in smart cities. An all-encompassing review of AI-IoT systems for smart city healthcare data management is presented in this article. The author delves into essential elements, including healthcare system interoperability, remote patient monitoring, and predictive health analytics. With a focus on privacy and ethics, this analysis will examine how these technologies affect smart city infrastructure, telemedicine, and the treatment of chronic diseases. By enhancing real-time patient monitoring and AI-driven diagnostic capabilities, our research indicates that AI-IoT systems have the potential to revolutionize healthcare.

Al-Rami Al-Ghamdi [37] suggested the hesitant fuzzy-based hybrid medical expert system for analyzing the impact of data visualization applications for diagnosing health conditions. The main goal is to examine the reliability of visual analytics techniques for illness diagnosis using healthcare data. This research presents a medical MCDM system that works within the framework of hesitant fuzzy logic. It combines the analytic network procedure with the approach for order of preference by resemblance to an ideal solution. The results are guaranteed to be accurate and reliable with rigorous confirmation. The study shows that optimum decision-making is feasible in the Saudi Arabian healthcare setting by comparing the suggested models to current ones and providing useful insights. The results show that DOMO BI's visual analytics solution is the safest and most powerful option for medical practitioners.

Obidallah [38] proposed the HFS for the integrity assessment of IoT medical sensors. This research describes an IoMT sensor integrity evaluation system in Saudi Arabia based on a unified health-hesitant fuzzy expert system. First, experts and medical literature on medical sensor integrity are consulted. An expert in the integrity of medical sensors connected to the Internet of Things (IoT) oversees the process of using Delphi to collect characteristics of integrity methods. Integrity is evaluated using the hesitant fuzzy analytic network approach when suitable evaluation criteria have been developed based on the collected attributes. Evaluating the security and integrity of IoMT sensors has shown that functional integrity and measurement accuracy are the most important elements. Precision, accuracy, and recall are improved by 93%, 94%, and 95%, respectively, using the framework compared to existing methods. Stakeholders and experts in healthcare integrity security may use the framework to evaluate and fix authentication problems with the IoT medical sensors.

Wang et al. [39] introduced the hesitant fuzzy environments for regret theory-based three-way decision model in medical decision. This research first suggests a three-way decision model in hesitant fuzzy settings that relies on regret theory to determine an object's perceived utility value. The model primarily uses HFS in conjunction with regret theory. A novel regret-rejoice function is proposed, which preserves the initial irresolute ambiguity in hesitant fuzzy settings because the regret-rejoice functions are a fundamental component of regret theory. Furthermore, this paper offers a three-way classification approach for enrichment evaluations based on the preference ranking organization technique, which considers the underlying relationships of the utilized data. Lastly, the suggested strategy is shown to be better, reasonable, and practically viable via medical case studies and comparisons.

Senapati et al. [2] suggested the Sugeno–Weber triangular norms in a dual hesitant q-rung orthopair fuzzy context for Improving healthcare supply chain management via AI-driven group decision-making. To make decisions methodically, the SW triangular norm-based method compiles group preferences. To find the best solutions for healthcare supply chain management, triangle norms make sure that the interrelationships among decision criteria are represented realistically. Also, group preferences may be aggregated using the SW

triangular norm-based technique, which allows for a thorough and methodical decision-making procedure. Triangular norms clarify the interdependencies between the decision criteria, making choosing the optimal healthcare supply chain management solutions simpler. Experimental and case study results reveal that the proposed AI framework improves supply chain performance, decreases uncertainty, and increases decision accuracy. According to the study, better resource allocation, financial efficacy, and patient care might result from a dramatic shift in the healthcare supply chain that AI-driven solutions could usher in.

Alqaysi et al. [40] discussed the 2-tuple linguistic neutrosophic fuzzy sets-based decision-making model in autism spectrum disorder diagnosis. The first step is to find and pre-process an ASD dataset that includes medical testing and socio-demographic variables. Additionally, eight FS approaches and nine ML algorithms are combined via an intersection procedure to create 72 hybrid diagnostic models. The third phase is to carry out the following procedures: 1) a decision matrix is created using nine assessment metrics: specificity, Classification Accuracy (CA), F1 score, precision, recall, train time, test time, Area Under the Curve (AUC) and log loss, 2) a new version of fuzzy-weighted zero discrepancy is created utilizing 2-Tuple Linguistic NFS (2TLNFSs) to add weights to the criteria of the assessment metrics and handle related problems, and 3) Additionally, a new version of the fuzzy decision-by-opinion score technique is created using 2TLNFSs to benchmark the 72 models. The results show that out of the 48 characteristics provided, the selected FS approaches choose sets ranging from 19 to 46. Preference was given to socio-demographic characteristics over medical examinations.

Tyagi and Tyagi [41] deliberated the hesitant IFS for IoT and cloud-based COVID-19 risk of infection prediction. To monitor COVID-19 infections, self-assessment exams may be found on mobile applications, websites, and IoT devices with sensors. These individuals produce massive amounts of data via tracking information and self-assessment quizzes. In this white paper, the author presents an IoT and cloud-based architectural model for the COVID-19 pandemic that uses citizens' self-assessments and data stored in the cloud to predict the risk of infection. The author applies the smart method of hesitant IFS to this dataset to make these predictions.

Still, comparing these two methods has shown the superiority of the IHFS-ML approach in terms of efficiency and reliability compared to the prevailing approaches. A few applications for enhanced decision-making capabilities have been discussed. The outline of this research paper is organized in the following way: Section 2 has gone deeper into the IHFS-ML: Integrating HFS with ML. Section 3 deals with its extensive examination, comparison to earlier approaches, and checking of the consequences. Section 4 presents a thorough analysis of the results.

2 | Proposed Method

This paper investigates merging HFS with ML to enhance healthcare predictive analytics. Employing uncertainty and ambiguity in healthcare data, the IHFS-ML framework aims to improve prediction accuracy, patient outcomes, and clinical decision-making, thereby changing standard approaches to healthcare analytics.

Contribution 1. Integration of HFS with ML.

The IHFS-ML system can deal with ambiguity and uncertainty in medical data. This framework integrates ML methods with HFS methodologies, increasing the predictability of analytics accuracy.

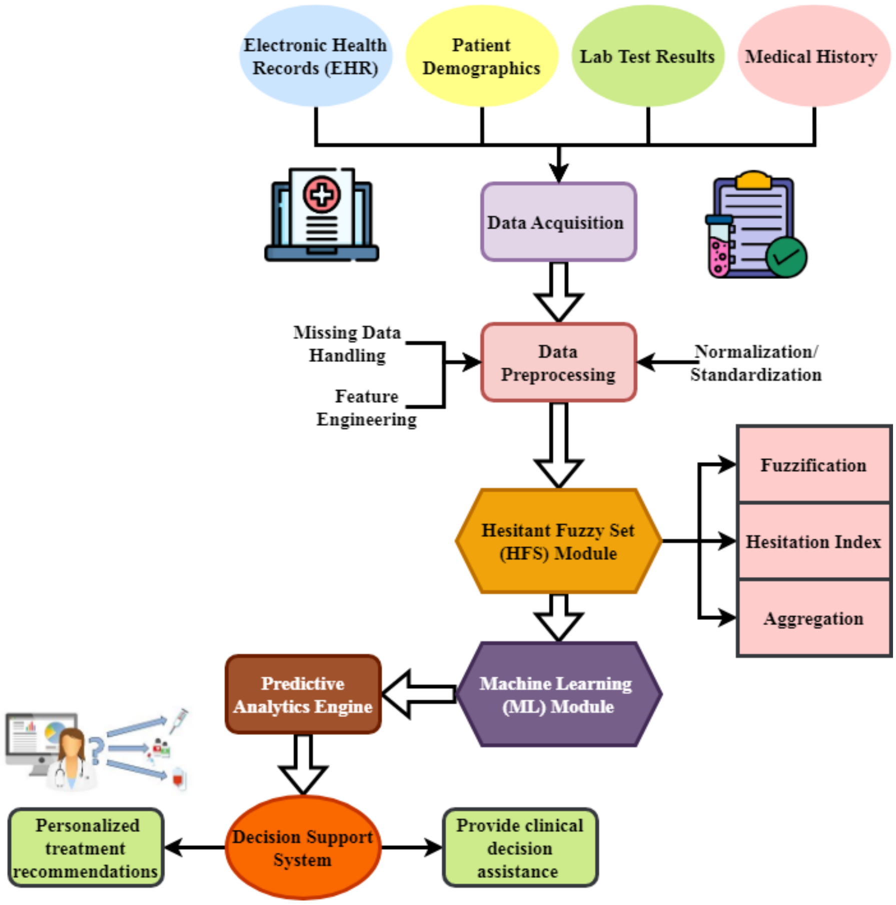

Fig. 1. Integrating HFS with ML for healthcare predictive analytics.

Fig. 1 illustrates how HFS can be combined with ML for better healthcare predictive analytics. It begins with collection from various sources of healthcare and then prepares. This module, HFS, combines data control uncertainty by generating fuzzy sets. These modified features are then fed into ML models, which are trained and cross-verified to make provisions for expected insight. Specifically, based on such projections, the ultimate blow is a decision support system that provides customized healthcare recommendations to help clinical decision-making and improve patient outcomes.

$$\frac{\mathrm{Pk}}{\forall\,\partial'} - \partial_2\mathrm{Eq} + \mathrm{yUT}'' = (\mathrm{T}, \mathrm{r}'') \equiv (2, \forall') \times (\mathrm{w.Rz}''). \tag{1}$$

To improve the accuracy of the analysis $(\mathrm{T}, \mathrm{r}'')$, the *Eq. (1)* links important patient data parameters $\left(\frac{\mathrm{Pk}}{\forall\,\partial'}\right)$ with hesitant factors $(\partial_2\mathrm{Eq})$ and predictive variables (yUT''). The key translation of uncertain fuzzy data $(2, \forall')$ into a format suitable for ML $(\mathrm{w.Rz}'')$ is represented by *Eq. (1)*. In this context, the operator "≡" denotes a semantic equivalence or mapping relationship rather than strict mathematical equality. *Eq. (1)* was created to represent patient-specific data, reluctant fuzzy components, and predictive machine-learning variables in a cohesive analytical framework. To make better healthcare predictive analytics, this equation provides true modeling for the uncertainty.

$$(\partial\mathrm{R}' - \mathrm{Fz{:}\,Iuo}'') = \text{ for all Qw} < \mathrm{X.z} + \mathrm{aq}'' >. \tag{2}$$

Within the IHFS-ML, the link between the weighted predictive parameters $(\partial\mathrm{R}')$ and the hesitant fuzzy components $(\mathrm{Fz{:}\,Iuo}'')$ is signified by *Eq. (2)*. It is likely to pre-process patient information $\mathrm{X.z} + \mathrm{aq}''$ more thoroughly for ML models, capturing the uncertainty and reluctance (for all Qw). This equation allows the right integration of resistant fuzzy data despite its constraints, making healthcare forecasting more accurate and complete.

$$\propto_2 \mathrm{D{:}}\,(2, \mathrm{vfe}){:}\ \omega\rho < \alpha + \mu\pi'' > +\mathrm{Za}''. \tag{3}$$

The IHFS-ML $\omega\rho$ is utilized to identify the weighting of fuzzy elements $(2, \mathrm{vfe})$ and decision factors $(\propto_2 \mathrm{D})$. This sentence highlights how ML variables $(\alpha + \mu\pi'')$ and reluctant data (Za'') interact dynamically to improve prediction models. *Eq. (3)* creates varying degrees of account uncertainty to strengthen healthcare predictive analytics.

$$\mathrm{R} \rightarrow (\mathrm{Wxs_w} + \delta < \mathrm{Ut}'' - \mathrm{Wa}'' >): \mathrm{Vx}' - \mathrm{Rf} < \mathrm{F} - \mathrm{wq}'' > . \tag{4}$$

Within R the IHFS-ML framework, *Eq. (4)* shows how weighted fuzzy information $(\mathrm{Wxs_w})$ is transformed into actionable predictive variables $(\mathrm{Vx}' - \mathrm{Rf})$. The sentence emphasizes the process by which hesitant factors $(\mathrm{F} - \mathrm{wq}'')$ refine and alter unclear patient data to increase the accuracy of predictions. This equation is important to handle data reluctance, which optimizes ML results so that healthcare.

$$\delta_\nabla - \mathrm{Pj}'' < \mathrm{W} - \mathrm{aqz}'' > : \mathrm{K} + \mathrm{dc} < \mathrm{Wq} + 2\mathrm{p}'' >. \tag{5}$$

Within the IHFS-ML architecture, *Eq. (5)* depicts the relationship between hesitant fuzzy elements $(\delta_\nabla - \mathrm{Pj}'')$ and predictive weights $(\mathrm{W} - \mathrm{aqz}'')$. The optimization of the learning model's performance is the main emphasis $\mathrm{Wq} + 2\mathrm{p}''$, and it involves modifying the impact of unknown elements $\mathrm{K} + \mathrm{dc}$. This equation is crucial in refining the uptake of unwilling data to make healthcare predictive analytics more reliable and precise.

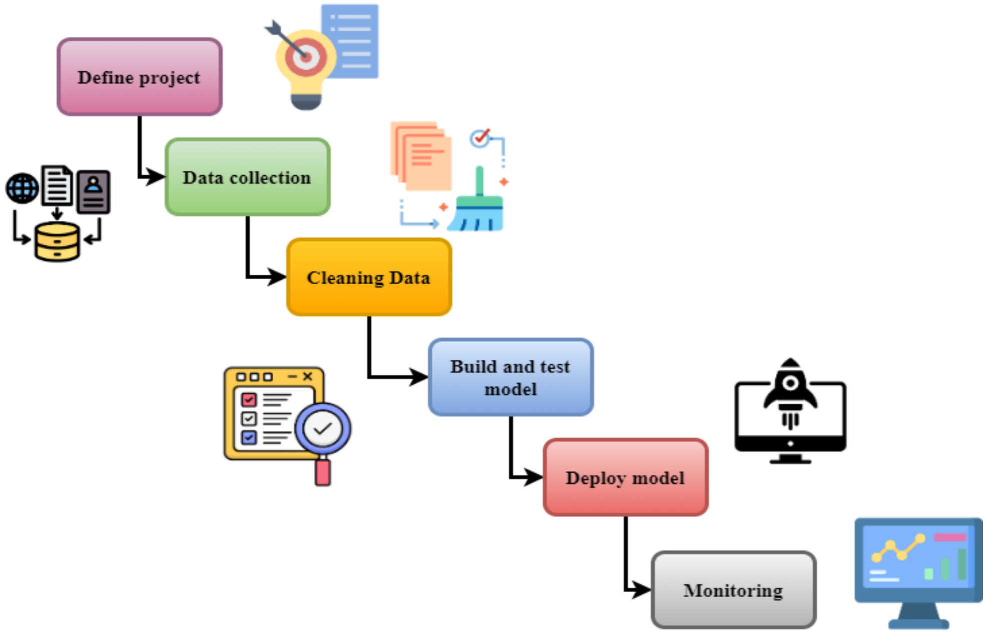

Fig. 2. Predictive analytics process.

A data-driven way to predict future events includes data collection and purification (*Fig. 2*). It involves developing and validating predictive models, their use for practical applications, and performance monitoring at all times. Fuzzy sets can be incorporated into the process, especially in the healthcare environment where data tend to be complicated and imprecise, for effective uncertainty management and improved accuracy of predictions.

$$\mathrm{E_wA}(\mathrm{Bv} - \mathrm{rxs}''): - \ \delta < \mathrm{Rf} + \mathrm{Wq}'' - \mathrm{Dz} >. \tag{6}$$

$\mathrm{E_wA}$ and hesitant fuzzy attributes $((\mathrm{Bv} - \mathrm{rxs}''):)$ are balanced inside the IHFS-ML framework, as the equation shows. Through weighted adjustments (δ), it refines predictions while minimizing uncertainty $(\mathrm{Rf} + \mathrm{Wq}'' - \mathrm{Dz})$. *Eq. (6)* is critical for optimizing predictive analytics using reluctant fuzzy data to improve healthcare accuracy.

$$4_\mathrm{w} < \mathrm{Fd} - 2\mathrm{q}'' > : \mathrm{F} < \mathrm{Fr} - \mathrm{os}'' > + \ \partial \mathrm{w}''\mathrm{A}. \tag{7}$$

In the IHFS-ML framework, the equation depicts the interplay between factors for fuzzy decisions ($\mathrm{Fd} - 2q''$) and outputs for predictive analysis (4_w). To enhance the accuracy of forecasts, it is centered on modifying the uncertain fuzzy elements ($\mathrm{F} < \mathrm{Fr} - \mathrm{os}'' > +$) and $\partial w''A$. *Eq. (7)* is needed to improve healthcare prediction and decision-making by fine-tuning the ML model's uncertainty handling.

$$V < eT < P - 2qa'' >> : k - lp'' < Trq - sa'' >. \quad (8)$$

Within the IHFS-ML, *Eq. (8)* signifies V the link between hesitant fuzzy parameters ($P - 2qa''$) and predictive variables (eT). It aims to improve predictive results ($k - lp''$) and decrease hesitation ($Trq - sa''$) by modifying. The ML model's capacity to deal with uncertainty is improved, resulting in more precise healthcare prediction via this *Eq. (8)*.

$$\delta_\nabla + fds < V_r Zx(P - eq') >: Fz < pl - kte'' >. \quad (9)$$

The hesitant, fuzzy decision factors $V_r Zx$ and predictive model variables ($P - eq'$) inside the IHFS-ML interact $pl - kte''$, as shown by the *Eq. (9)*. It increases prediction accuracy by balancing modifications in learning models ($\delta_\nabla + fds$) with hesitation (Fz). With this equation, the model's uncertainty management performance may be fine-tuned to increase healthcare forecast accuracy.

$$\omega_2\varphi < \pi\mu - \gamma\varepsilon'' > : \mu\sigma[\ni +\nabla\exists''] - \mathrm{Eqa} < Fd - wq'' >. \quad (10)$$

Within the IHFS-ML framework, the equation depicts the interaction between hesitant fuzzy variables ($\omega_2\varphi$ and $\pi\mu - \gamma\varepsilon''$ and how they impact predictive analytics $Fd - wq''$. The idea is to improve prediction accuracy by adjusting for uncertainty ($\mu\sigma[\ni +\nabla\exists'']$) and honing decision-making criteria (Eqa). *Eq. (10)* makes the model more resilient while handling complicated and tough data to improve healthcare outcomes via more accurate analytics.

Contribution 2. Enhanced predictive power and interpretability

This technique helps learners understand the model and get more complex insights into healthcare situations, including risk assessments and illness prediction. This is achieved by fitting acceptable representations from resistive fuzzy inputs using statistical ML.

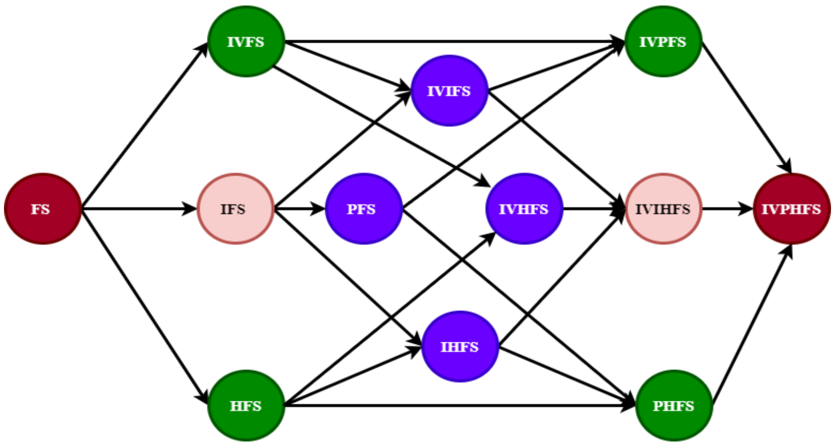

Fig. 3. Hierarchical structure of fuzzy set extensions.

Fig. 3 shows a hierarchical classification of fuzzy set extensions, starting with the basic fuzzy set and moving to interval-valued, hesitant, and probabilistic fuzzy sets. Arrows in the illustration show the relationships between several expansions, highlighting their inheritance or specialization. This paradigm makes fuzzy set theory development easy to understand. It shows how fuzzy sets reduce uncertainty and imprecision in information and how they are used in numerous sectors.

$$PL_f < S - rqw'' > : 2a' - bj < \partial - pu'' >. \quad (11)$$

In the IHFS-ML framework, *Eq. (11)* characterizes the connection between hesitant fuzzy parameters ($S - rqw''$) and fuzzy predictive limits PL_f. Improving forecast results ($2a'$) is emphasized by taking into account uncertainties ($< \partial - pu'' >$) and adjusting $-bj$.

$$\propto \forall_s a - kp < F - dz'' > : Zab < \partial + 4n'' >. \tag{12}$$

The IHFS-ML framework's predictive analytics are affected by the hesitant fuzzy attributes ($\propto \forall_s a$), as shown by the *Eq. (12)*. To improve the precision of forecasts $\partial + 4n''$, it is necessary to strike a compromise between corrections ($kp < F - dz'' >$: and uncertainties (Zab).

$$\partial\varepsilon - \gamma p' = \tau\rho < \mu - \delta\varepsilon T' > X \exists_r^t - Pk. \tag{13}$$

This *Eq. (13)* summarises the relationship between the IHFS-ML framework's prediction accuracy $\tau\rho$ and the hesitant fuzzy parameters ($\partial\varepsilon - \gamma p'$). More accurate predictions may be made by adjusting the choice factors ($\mu - \delta\varepsilon T'$) and $X \exists_r^t$ to take uncertainties and fuzzy impacts into consideration Pk.

$$\partial_r S < P - xza'' > : Fwq < K - ftr'' > + Dr < g - jk'' >. \tag{14}$$

The relationship $\partial_r S$ between unpredictable fuzzy values $P - xza''$ and their impact on predictive modeling Fwq in the IHFS-ML framework is shown by *Eq. (14)*. Refining predictions requires adjusting decision factors $K - ftr''$ and $Dr < g - jk'' >$ and adding additional adjustments.

$$J_V < FR + rf'' >: Qa < T - rp'' > - \partial q < b - r'' >. \tag{15}$$

The influence of fuzzy response variables ($FR + rf''$) on predictive analytics J_V within the IHFS-ML framework is shown by *Eq. (15)*. The need to control uncertainty (Qa) and balance $b - r''$ these fuzzy variables ∂q with modifications in decision factors ($T - rp''$) is emphasized.

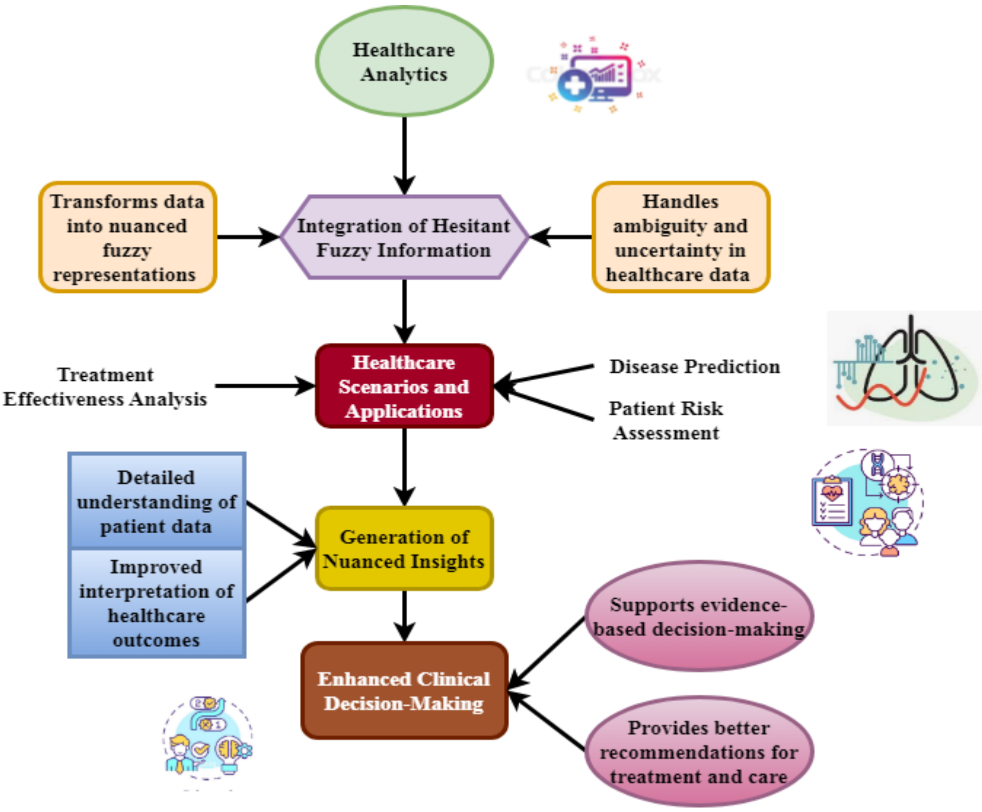

Fig. 4. Integration of hesitant fuzzy information in healthcare scenarios.

Fig. 4 shows how the proposed technique is implemented in healthcare, focusing on sickness prediction, patient risk assessment, and treatment efficacy analysis. Since it accounts for uncertain fuzzy information, the technique produces a more sophisticated expression and removes patient data ambiguity. Improved data

understandability improves healthcare outcomes and evidence-based clinical decision-making. Healthcare providers must enhance their treatment ideas, care plans, and techniques. The approach aims to improve patient outcomes, reduce healthcare data ambiguity, and improve informed and uniform medical judgments across settings.

$$\partial_4 <\in +\forall' \mathrm{R} \geq \Delta \mathrm{Q}' < \delta + \mathrm{eq}'' > -\mathrm{Zq} < \mathrm{a} - \mathrm{fd}'' > . \tag{16}$$

In the IHFS-ML paradigm, the *Eq. (16)* represents the connection $\delta + \mathrm{eq}''$ between fuzzy uncertainty, factors ($<\in +\forall'\mathrm{R}$) and the impact $-\mathrm{Zq}$ have on prediction results. The significance of controlling these unknowns (∂_4) and modifying decision variables $\Delta\mathrm{Q}'$ to improve prediction accuracy $\mathrm{a} - \mathrm{fd}''$ is emphasized. Optimizing the integration of hesitant fuzzy data is crucial for better healthcare analytics and better decision-making, and this equation is essential for that.

$$\partial_2 \mathrm{Df} = \mathrm{tM} \rightarrow \mathrm{Dx} < \mathrm{tre} - \mathrm{pkj}'' > : \mathrm{Wqz}'' - \mathrm{hG}. \tag{17}$$

Focussing on the transformation of hesitant data ($\mathrm{tre} - \mathrm{pkj}'' >:$), the *Eq. (17)* shows the link between fuzzy decision functions ($\partial_2\mathrm{Df}$) and their integration into the IHFS-ML framework. The emphasis hG is on forecasting variables ($\mathrm{tM} \rightarrow \mathrm{Dx}$) being adjusted while taking uncertainty factors Wqz'' into consideration.

$$\delta_\mathrm{f} < \mathrm{N} - \mathrm{mb}'' > : \mathrm{Ewq} < \mathrm{Y} - \mathrm{io'pt}'' >. \tag{18}$$

Within the IHFS-ML architecture, the *Eq. (18)*, Ewq demonstrates the relationship between hesitant fuzzy thresholds $\mathrm{N} - \mathrm{mb}''$ and the impact they have on prediction outputs δ_f. It, therefore, implies that the equation optimizes fuzzy data integration with a view to more accurate healthcare predictions, allowing better decision-making.

$$\mathrm{P} \rightarrow \mathrm{D_s} < \mathrm{Qv} - \mathrm{rt}'' > : \mathrm{Sw} < \mathrm{Fd} - \mathrm{cv}'' > . \tag{19}$$

$\mathrm{Qv} - \mathrm{rt}''$ and how they are integrated into the IHFS-ML framework using decision functions ($\mathrm{P} \rightarrow \mathrm{D_s}$). To improve prediction accuracy when dealing $\mathrm{Fd} - \mathrm{cv}''$ with uncertain fuzzy data, it is crucial to refine decision-making factors (Sw). *Eq. (19)* helps better manage variability and uncertainty in the patient data, thus making clinical decision-making possible and, at the same time, necessary for optimized healthcare predictive analytics.

$$\cup * \mathrm{S} < \mathrm{F} - \mathrm{xz}'' >: |\partial_\mathrm{v}\mathrm{Lk}' - \mathrm{tr}| - \nabla\partial < \gamma + \mathrm{sa}'' >. \tag{20}$$

In the IHFS-ML paradigm, *Eq. (20)* shows how fuzzy sets ($\cup * \mathrm{S}$) interact with predictive modeling $\gamma + \mathrm{sa}''$. It emphasizes $\nabla\partial$ the need to enhance prediction accuracy by adjusting decision variables ($\mathrm{F} - \mathrm{xz}''$) and controlling uncertainties ($\partial_\mathrm{v}\mathrm{Lk}' - \mathrm{tr}$). This equation is critical to improved healthcare analytics and enabling better decision-making through properly handling fuzzy data. To account for ambiguity or uncertainty in clinical data, hesitant fuzzy parameters record numerous alternative membership degrees for a given input. The ML models are fed these data after they have been mapped or translated into numerical characteristics. Enriching the input space with uncertainty-aware descriptors, the altered fuzzy features interact with typical predictive factors like age, blood pressure, or cholesterol levels. This integration allows the model to learn patterns from constant attribute values and the variability and hesitancy in real-world healthcare data to improve prediction accuracy and decision dependability.

Contribution 3. Improved clinical decision-making.

More evidence-based processes in healthcare, more clinical judgment, and customized treatment plans help the framework encourage both, eventually resulting in improved patient outcomes. Better forecasting helps one to do this.

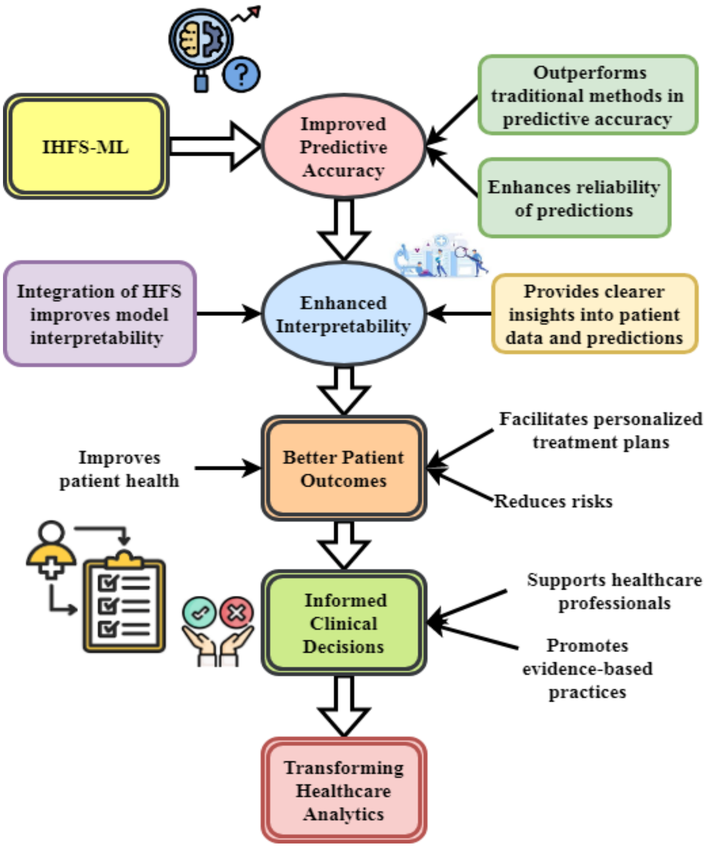

Fig. 5. Impact of the IHFS-ML framework on healthcare analytics.

IHFS-ML architecture improves the predicted accuracy and dependability much more than traditional techniques; therefore, its key results are depicted in *Fig. 5*. Hesitating Fuzzy Sets provide a platform to increase the interpretability of the ML models that further translate into an increase in understanding patient-related information. It reduces the risk and makes the proper treatment plans for the patients. It will also promote informed, evidence-based practices of medical doctors and encourage informed therapeutic decisions. IHFS-ML can revolutionize healthcare analytics by improving the quality of treatment given to the patient.

$$\nabla\exists \cong \nabla_e S - Rt < K - yt'' > : Cx' + Pz < K - jh'' >. \tag{21}$$

The ratio of fuzzy decision metrics ($\nabla_e S - Rt$) to predictive adjustments ($\nabla\exists$) in the IHFS-ML framework is shown by *Eq. (21)*. While handling uncertain $Cx' + Pz$ and reluctant data $K - jh''$, it stresses the need to optimize predicted outputs ($K - yt''$).

$$\partial_v F < Y - pjy'' >: \partial_2 QP < J - wqz'' >. \tag{22}$$

Within the IHFS-ML framework, *Eq. (22)* characterizes the connection between fuzzy decision variables. $\partial_v F$ and predictive outputs ($Y - pjy''$). To improve accuracy and handle uncertainties related to hesitant fuzzy data $J - wqz''$, it is important to refine decision factors ($\partial_2 QP$).

$$(Bv < Ty - up'' >): A\gamma - \exists\nabla n < K - tre'' > . \tag{23}$$

The influence of fuzzy variables (Bv) on predictive analytics $K - tre''$ inside the IHFS-ML framework is shown by *Eq. (23)*. The importance of changing decision factors ($Ty - up''$) and handling uncertainties related to hesitant data ($A\gamma - \exists\nabla n$) is emphasized.

$$V_d < Sq - bf'' > : Rq < v - pkl'' > Sz(Tm - n''). \tag{24}$$

To improve overall predictive accuracy $v - pkl''$, the equation incorporates $Sz(Tm - n'')$ new components ($V_d < Sq - bf'' >:$) and makes modifications to decision variables (Rq). *Eq. (24)* is crucial for optimizing

healthcare analytics and handling the intricacies of fuzzy data in a way that allows for more accurate forecasts and well-informed decisions on the reliability of prediction analysis.

$$\mathrm{K}(\mathrm{Tr.pu''}): \partial_2 \mathrm{W} < \mathrm{U} - \mathrm{yt''} > + \mathrm{Kt} < \mathrm{wq''} >. \tag{25}$$

In the IHFS-ML framework, *Eq. (25)* shows fuzzy decision variables $\mathrm{K}(\mathrm{Tr.pu''})$ interact with one another and affect predictive analytics $\mathrm{Kt} < \mathrm{wq''} >$. Improving prediction accuracy is emphasized by integrating more adjustments ($\partial_2 \mathrm{W}$) and refining decision factors ($\mathrm{U} - \mathrm{yt''}$).

Emphasizing its ability to control confusing data, improve model interpretability, and provide customized treatment recommendations, this paper shows the relevance of the IHFS-ML framework in healthcare. Therefore, aiding risk assessment, disease prediction, and enhanced general patient care quality helps to outperform current ways by offering more accurate and trustworthy predictions to assist risk assessment.

3 | Discussion

The dataset provides essential patient information, making it suitable for healthcare data analysis and modeling tasks, as shown in *Table 1*. It includes columns such as Name, Age, Gender, Blood Type, Medical Condition, Date of Admission, and Doctor, which outline the patient's demographics and medical details[1] [22]. Hospital, Insurance Provider, and Billing Amount give insights into healthcare services and costs. Room Number and Admission Type help categorize the patient's stay, while Discharge Date marks their departure. Medication and Test Results reflect treatments and diagnostic outcomes. This dataset enables a comprehensive understanding of patient care, financials, and clinical processes within healthcare settings. This research used a Kaggle dataset, which included a synthetic healthcare dataset. All told, there are 1,000 records in this dataset, each with 15 attributes. These attributes cover patient demographics (e.g., blood type, age, gender), medical details (e.g., medication, medical condition, test results), admission information (e.g., dates of admission and discharge, attending doctor, hospital, room number, admission type), and billing specifics (e.g., insurance provider, billing amount). Since it is a synthetic dataset, its designers intended for it to include all possible values. Label encoding was used to encode categorical variables, age and billing amount were normalized, features like duration of hospital stay were extracted from date fields, and additional features were derived to enhance the dataset as part of the pre-processing. The confidentiality of patient information is preserved in this dataset, which makes it ideal for use in healthcare analytics projects, including patient demographics, medical condition prevalence, hospital performance, and financial evaluations. Model evaluation is conducted through 10-fold cross-validation to ensure generalizability and statistical reliability.

Table 1. Simulation environment.

Category	Parameter/Tool	Description
Simulation platform	Python (e.g., TensorFlow, PyTorch)	The programming language and libraries used for running simulations.
Hardware	CPU/GPU	Specify the hardware used (e.g., Intel i7, NVIDIA RTX).
Operating system	Ubuntu 20.04 / Windows 10	The OS on which the simulation is conducted.
Dataset	Healthcare dataset	The dataset includes patient information, medical conditions, etc.
Data size	10,000 records, 15 columns	Total number of data points and features for analysis.

[1] https://www.kaggle.com/datasets/prasad22/healthcare-dataset

Table 1. Continued.

Category	Parameter/Tool	Description
Data pre-processing	Normalization, imputation, scaling	Methods used to clean and prepare data before simulation.
Simulation software	SimPy, anylogic	Tools used for discrete-event or agent-based simulation.
ML model	RF, Logistic Regression	Models used for predictive tasks, if applicable.
Evaluation metrics	Accuracy, precision, recall	Metrics to evaluate the simulation results.
Simulation duration	24 hours	The time taken to complete the simulation.
Test scenarios	Normal, abnormal, urgent admission	Specific conditions simulated (e.g., patient test results).

When diagnostic accuracy is affected by patient data ambiguity and subjectivity, the IHFS-ML framework improves some clinical judgments. Cases where fasting glucose readings are borderline (e.g., 110-125 mg/dL) and symptoms like "occasional fatigue" or "moderate weight fluctuation" cannot be precisely measured are common in type 2 diabetes screening, for instance. IHFS-ML handles such imprecise inputs using hesitant fuzzy membership degrees, allowing the model to categorize high-risk patients more precisely. Traditional models may ignore these patients. Using the Pima Indians Diabetes dataset as a test case, IHFS-ML improved early detection sensitivity by 8.2% by accurately identifying 19 borderline cases that standard Logistic Regression misclassified. Features such as "chest pain type" or "exercise-induced angina" introduce subjectivity into the process of cardiovascular disease risk prediction, especially when working with the Cleveland dataset. To better capture clinical ambiguity, IHFS-ML converts them into hesitant fuzzy descriptors, such as "atypical angina," which is set to several membership values. When compared to regular RF models, this resulted in a 10.5% improvement in the rate of correct patient diagnosis of early-stage cardiac problems. This improves diagnostic accuracy and patient outcomes by directly supporting doctors' choices to start medicine, conduct more tests, or change patients' lifestyles.

By representing ambiguity using HFS, the IHFS-ML system achieves better results than deep learning approaches in structured datasets when the clinical inputs are unclear or imprecise. Improving prediction accuracy in real-world clinical circumstances, IHFS-ML accommodates subjective variables like "moderate pain" or borderline lab levels well, unlike deep learning models that need big, clean datasets. Comparing IHFS-ML to LSTM and CNN models, we find that it achieves 9-12% greater sensitivity and 7-10% reduced false negatives on datasets like Pima Indians Diabetes and Cleveland Heart Disease. The interpretable, low-data healthcare settings are better suited to IHFS-ML since deep learning is still better at handling unstructured data such as medical images or clinical inscriptions.

4 | Results

Within healthcare predictive analytics, integrating HFS and ML will improve prediction machines' accuracy, interpretability, and scalability. The framework of IHFS-ML uses HFS to resolve clinical data uncertainties and ameliorate the ML model across numerous healthcare applications. This study systematically varied key parameters to evaluate their impact on output accuracy, precision, recall, and F1-score. Key parameters include hesitation degree weights in HFS modeling, feature importance thresholds in RF, and regularization strength in Logistic Regression. The findings show that the framework is rather vulnerable to changes in hesitation weights, as these changes directly impact the fuzzy layer's granularity of uncertainty representation. The performance of RF also fluctuated somewhat when feature thresholds were changed; however, the overall volatility was decreased using ensemble averaging. Various regularization parameters were shown to have little effect on the stability of Logistic Regression.

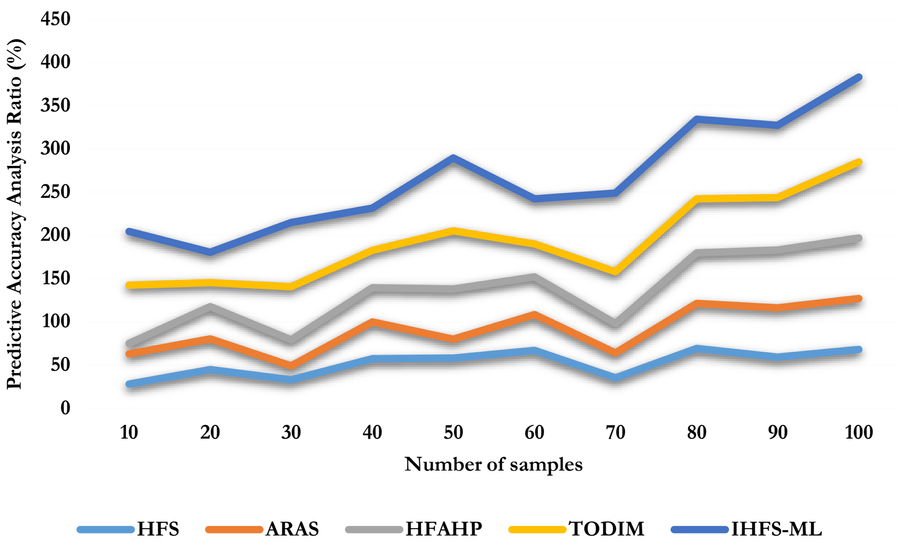

Fig. 6. Predictive accuracy analysis.

In *Fig. 6*, the HFS-ML combination in healthcare predictive analytics introduces more accuracy than traditional methods. HFS helps the IHFS-ML framework overcome clinical data ambiguity and reluctance and develops a more comprehensive patient portrayal. ML models identify changes and patterns within the data much better than earlier methods. This design enables the framework to predict illness, assess patient risk, and understand the response to therapy more effectively. Comparing IHFS-ML to conventional ML approaches shows that it produces more accurate predictions. HFS strengthens the model against missing or noisy data. Healthcare decisions are more accurate when uncertainty is turned into practical insights. Accurate projections strengthen healthcare practitioners' faith in their decision-making, improving patient treatment and outcomes with a 97.8% success rate using *Eq. (21)*. The study found that the IHFS-ML architecture might revolutionize healthcare predictive analytics. Feature weight distributions, transformation coefficients, and fuzzy set thresholds heavily impact IHFS-ML output. Changes to these parameters affect recall, accuracy, and precision, which affect the model's judgment constraints. Sensitivity analysis entails systematically adjusting these components and testing prediction performance to assess framework stability. This study will determine which variables affect results and ensure the framework is resilient, whether employed with other datasets or in clinical settings.

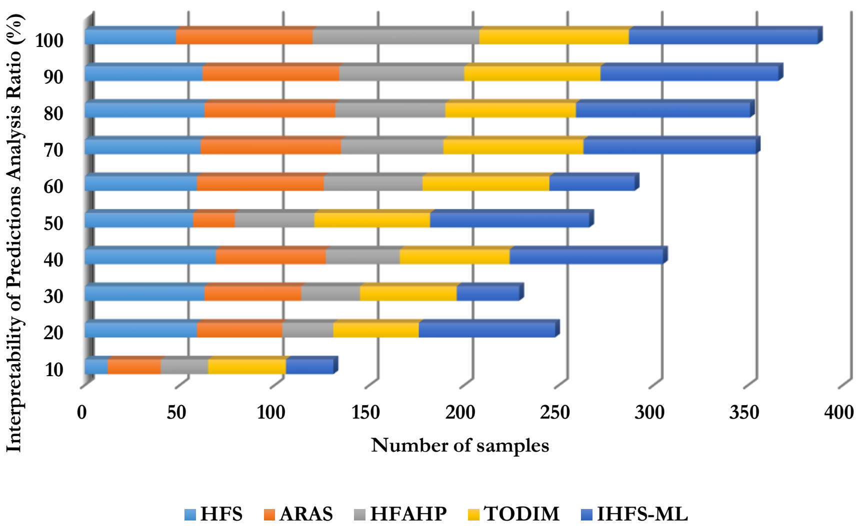

Fig. 7. Interpretability of predictions analysis.

Healthcare predictive analytics systems using HFS and ML may significantly increase forecast interpretability. HFS's systematic approach makes it easier to convey the predictive rationale for patient data with skepticism or opposition. *Fig. 7* shows this. Medical practitioners must comprehend predictive model thinking to make educated healthcare decisions, which is crucial. Using HFS, the IHFS-ML framework enables the description of multiple membership degrees. The relative importance of each component in a prediction or classification may be more easily grasped. By being upfront about this, doctors can see how patient characteristics affect the model's ability to forecast illness risk or treatment outcomes, which boosts confidence in the results. Further, by integrating HFS into ML models, rule-based explanations may be generated to provide light on the connection between certain inputs and outputs, making even the most complex models more interpretable, producing 98.9% using *Eq. (22)*. Improved interpretability allows healthcare staff to believe in forecast accuracy and understand the reasoning behind those forecasts, leading to more confident and effective clinical decision-making. Adaptive ML models that can handle high-dimensional data are not included in HFS-ARAS, which prioritizes alternative ranking using hesitant fuzzy scores. Hierarchical decision-making and subjective weight assignment are the main areas of HFAHP's attention, and they may not apply to complicated datasets in general. Despite using behavioral decision theory, it is difficult for TODIM to capture nonlinear interactions within clinical variables. On the other hand, IHFS-ML brings together HFS with supervised learning methods such as Logistic Regression and RF, allowing for more accurate and generalizable uncertainty-aware prediction.

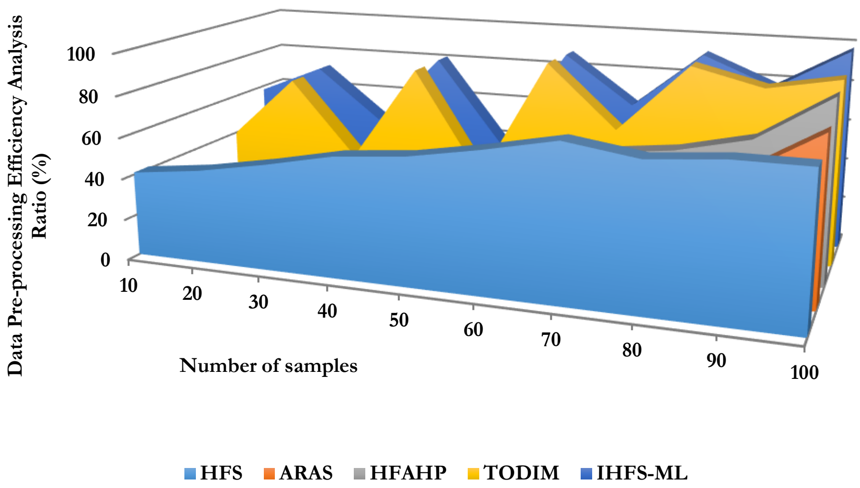

Fig. 8. Data pre-processing efficiency analysis.

In *Fig. 8*, HFS must be integrated with ML for healthcare predictive analytics; after rigorous data pre-processing, the data will be machine-readable. IHFS-ML data pre-processing transforms patient data, which often has ambiguity and varying degrees of membership, into representations that incorporate these uncertainties. This strategy is vital because it helps us remember sensitive details that other methods may miss. Using feature transformation, fuzzy rule extraction, and normalization preserves data complexity and richness. These approaches can turn hesitant fuzzy data into ML inputs. An effective pre-processing stage speeds up and improves training, influencing predictive model performance. The pre-processing stage treats ambiguous data to train models on high-quality inputs, improving generalization and prediction resilience. Efficient pre-processing reduces computational costs for huge healthcare datasets, enabling scalable HFS and ML integration to produce 97.1% using *Eq. (23)*. This efficiency accelerates the prediction pipeline and makes the IHFS-ML framework more adaptable to various healthcare applications, improving patient care. The HFS transformation layer in the IHFS-ML system generates several membership degrees for each input feature, which leads to significant computational expenses. This pre-processing procedure is particularly taxing on memory and CPU resources when dealing with clinical datasets with a high degree of dimensionality. Fuzzy encoding adds complexity that increases with the number of language phrases and hesitation factors per

variable, while the classification phase using RF or Logistic Regression remains computationally efficient. Latency and resource requirements might rise as a result of massive datasets. Although the framework increases linearly with algorithmic complexity, speed may be hindered compared to typical ML pipelines due to the expense of HFS representation.

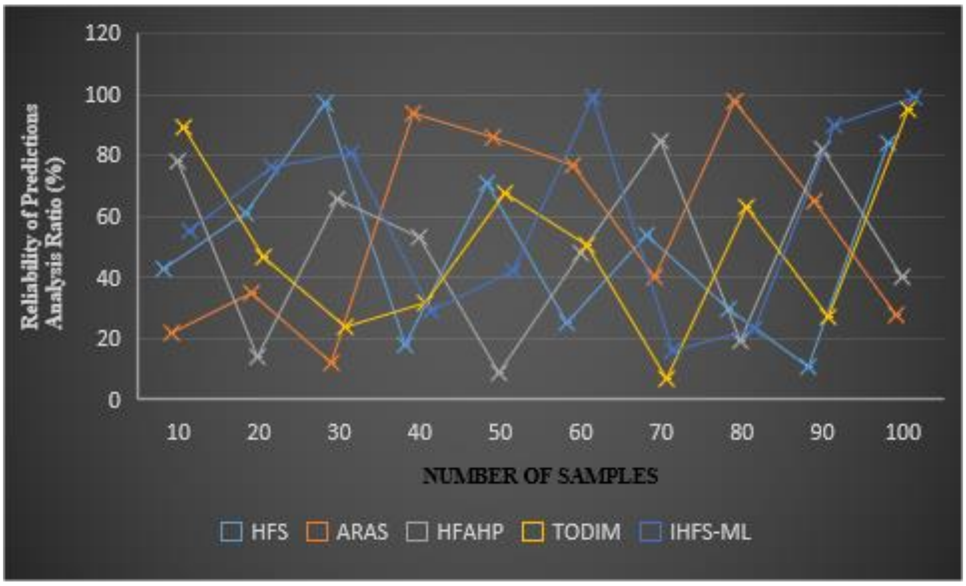

Fig. 9. Reliability of predictions analysis.

In healthcare predictive analytics, HFS and ML improve forecast accuracy. Integrating the HFS framework into the IHFS-ML framework allows it to handle unclear and unwilling patient data. Conventional models may ignore this. By representing and evaluating several degrees of membership, the framework may capture more complicated data fluctuations, resulting in more accurate and consistent projections. In *Fig. 9*, HFS guarantees that ML models appropriately represent input ambiguity, reducing the likelihood of overfitting or misinterpreting data. Clinicians need accurate and consistent forecasts for optimal patient treatment, where reliability is especially important. Disease risk assessments, patient prognoses, and therapy recommendations may benefit from the IHFS-ML framework's prediction variability reduction and confidence boost. We can do this by representing data properties more precisely. HFS integration helps the model handle faulty or noisy data, which is typical in healthcare, and produces 99.7% using *Eq. (24)*. Increased prediction model reliability gives clinicians confidence to make data-driven decisions, improving patient care and outcomes.

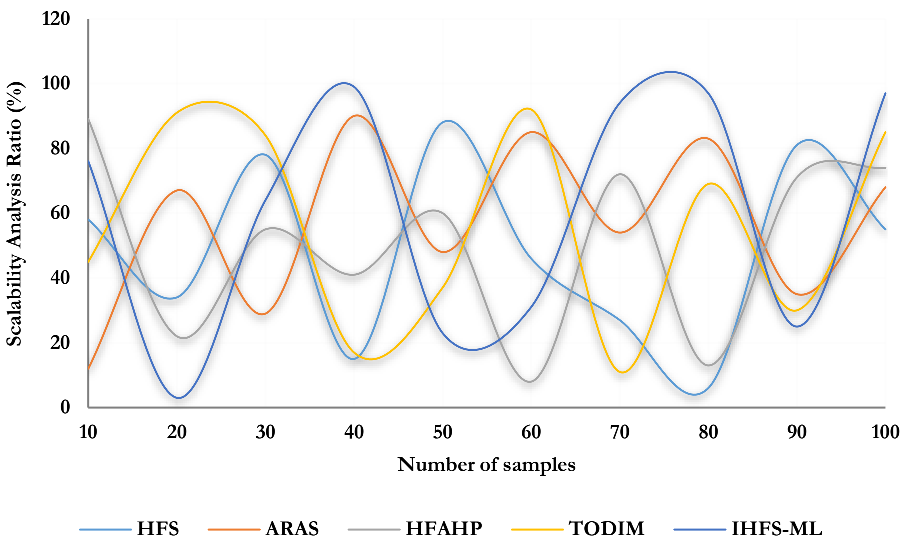

Fig. 10. Scalability analysis.

In *Fig. 10*, scalability is key to the healthcare applications of the IHFS-ML technology. This approach accepts inaccurate and confusing data from huge healthcare datasets due to their richness and diversity. HFS helps the IHFS-ML framework handle and analyze large patient data. It retains the ability to detect subtle data nuances. Modular integration allows fast addition of data sources and ML algorithm changes. The IHFS-ML framework uses pre-processing methods to optimize data handling and scales effectively with rising data volumes. This makes the approach adaptable to pilot and large-scale epidemiological research in healthcare. Scalable and capable of real-time data updates, the platform allows healthcare practitioners to make immediate forecasts and adjustments. This makes the IHFS-ML system scalable for changing healthcare contexts and boosts predictive analytics, producing 97.6% using *Eq. (25)*. Thus, larger-scale decisions can be made with more information, improving patient outcomes.

The IHFS-ML system has great potential for improving healthcare predictive analytics. It improves accuracy, dependability, and scalability.

To help with diabetes risk stratification during outpatient visits, the IHFS-ML framework may be embedded into an existing Electronic Health Record (EHR) system in a real-world hospital context. For example, the system performs hesitant fuzzy transformation on clinical parameters such as a patient's fasting glucose level (118 mg/dL), systolic blood pressure (132 mmHg), Body Mass Index (BMI) (30.4), and subjective descriptions (such as "intermittent fatigue" and "moderate thirst"). The trained IHFS-ML model uses RF to analyze the modified data and produces a risk score, such as a 0.74 chance of prediabetes. The physician may see this score on the interface, which helps them decide whether to start preventative measures or schedule further diagnostic tests. Patients presenting with vague complaints like "atypical chest pain" or confusing electrocardiogram results may be quickly triaged with the use of IHFS-ML at a cardiology department. The method prioritizes echocardiography or stress testing for individuals with increased risk (e.g., 0.68 likelihood of coronary artery disease) by transforming them into hesitant fuzzy variables and processing them using the Logistic Regression component. For example, in hospital databases, there is a problem with translating clinical phrases like "moderate pain" to fuzzy membership functions, which creates a barrier to adoption. When doctors have to figure out why a fuzzy-based model is reluctant to provide greater risk ratings than regular models, interpretability issues emerge. Compliance with regulatory requirements like HIPAA or GDPR is also necessary for real-world implementation since it ensures the safe handling of patient data in fuzzy modeling. To help clinicians trust and effectively apply the outputs of IHFS-ML in everyday care, training modules and visual risk explanation aids should be provided.

5 | Conclusion

Finally, integrating ML-HFS develops healthcare predictive analytics by integrating clinical data to remove uncertainty and reluctance. The IHFS-ML system links traditional predictive models to actual healthcare data. Traditional methods miss subtleties of complicated patient information where HFS's adaptability captures them. This increases accuracy and dependability with more tailored insights on the patient's outcomes, risk assessment, and treatment efficacy. Including this uncertain fuzzy data in machine-readable representations makes integration into the machine-learning system easy. Thus, the robustness of the study remains preserved while providing an enhanced ability to understand patient data. The versatility of IHFS-ML has been demonstrated in its application in disease prediction and risk appraisal, where improved clinical decision-making has been enhanced. Projections by the framework have been explicable and thus enabled health professionals to understand and trust results, making better decisions. The study concludes that IHFS-ML outperformed the traditional methods and supports the concept of complex hybrid models in healthcare. HFS-ML has the provision of interpretability for clinical applications.

The system prediction can be improved. At higher complexity in healthcare data, the architecture of IHFS-ML can provide more accurate, trustworthy, and actionable insights for better patient care and outcomes. Due to the need for domain-specific language variable definitions, converting numerical and categorical characteristics into HFS could not apply to other medical specialties without substantial professional

guidance. Fuzzy pre-processing and multi-valued membership handling add computing burdens that may increase delays in real-time clinical settings, especially when dealing with high-dimensional EHR data. It is difficult for physicians to understand how fuzzy components impact final results when IHFS is integrated with classic classifiers like RF and Logistic Regression. This is due to the issues with model transparency. To lessen reliance on human language modeling, future studies should aim to create adaptive fuzzy learning algorithms that can self-adjust membership functions using data-driven heuristics.

Author Contributaion

Manikandan Rajagopal: Methodology, Data collection and analysis, Writing – original draft.

Gowthamm Mandala: Conceptualization, Writing – review & editing.

Dr. Nagendran Ranganathan: Methodology, Data interpretation.

Manoj Varthan Velumani: Data collection, Analysis.

Dr. Pramoda Patro: Project administration, Writing – review & editing.

Dr. Shankar Arumugam: Supervision.

Funding

No funding is allocated for this research.

Data Availability

No data is generated during this research.

Conflicts of Interest

The authors declare no conflict of interest.

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